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Do countries influence neighbouring pollution? A spatial analysis of the EKC for CO_2 emissions

Roberto Balado-Naves*, José Francisco Baños-Pino, Matías Mayor

University of Oviedo, Spain

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ABSTRACT

By considering spatial relationships, this study aims to analyse to what extent per capita CO_2 emissions are determined by renewable energy consumption, the share of the services sector in GDP, energy intensity and real per capita income. A panel data set composed of 173 countries over the 1990–2014 period is used to estimate an environmental Kuznets curve (EKC) augmented by neighbouring per capita income and energy intensity. Both standard and spatial forms are estimated for seven different sets of countries to assess the robustness of the results. Finally, several forecasts are performed to verify global sustainability and to provide some policy suggestions for the period 2015–2100. The empirical results indicate that (i) most areas support the standard EKC, (ii) there seems to be an inverted U-shaped relationship between neighbouring per capita income and national per capita emissions in Europe, Asia and the World as a whole, (iii) neighbouring energy intensity increases national per capita emissions, and (iv) forecasts show that economic growth will accelerate climate change. However, a steady annual growth in renewable energy consumption and a steady decrease in energy intensity, both close to 2.5%, may guarantee environmental sustainability prior to 2100.

1. Introduction

According to the IPCC Fifth Assessment Report (2014), anthropogenic greenhouse gas (GHG) emissions have increased since 1750, leading to a situation where atmospheric concentrations of CO_2, CH_4 and N_2O have reached unprecedented levels over the past 800,000 years. The major contributor to GHG emissions, as well as the gas that remains longest in the atmosphere, is carbon dioxide -CO_2-. More precisely, 78% of total GHG emissions have been caused by CO_2 emissions for the 1970–2010 period, at the same time CO_2 concentrations have been increasing at their fastest observed decadal rate of change (2.0 ± 0.1 ppm/yr) for 2002–2011. Therefore, the threat of climate change is more intense than ever due to uncontrolled carbon dioxide emissions.

Carbon dioxide pollution is highly correlated to the usage of energy derived from exogenous sources to manpower; more specifically, to fossil fuel consumption. Since the Industrial Revolution, the increasing production scale and needs of trade of Western countries required new forms of automated production and faster transport. This would probably not have been possible without the development of better techniques that seized the energy potential of fossil fuels, such as coal in the first stages, or petroleum and natural gas in the mid-late nineteenth century. In this regard, recent economic literature has pointed out the importance of growing and non-decreasing trade relationships around the world. More precisely, Jones and Romer (2010) state that "Increased flows of goods, ideas, finance, and people—via globalisation, as well as urbanisation—have increased the extent of the market for all workers and consumers. (…) World trade as a share of GDP has nearly doubled since 1960". Previous EKC studies have also noted that international trade may be a key factor for explaining changes in CO_2 emissions (e.g. Roberts and Grimes, 1997; Friedl and Getzner, 2003; Halicioglu, 2009; Ertugrul et al., 2016). Therefore, it seems reasonable to study to what extent the increasing globalisation has impacted in economic growth, energy consumption, CO_2 emissions and, eventually, in world's environmental sustainability.

The aim of this paper is to analyse the relationship between economic growth and carbon dioxide emissions in 173 countries during the 1990–2014 period yet paying special attention to the influence of globalisation on it. To do so, we test the existence of spatial spillovers in the traditional CO_2 EKC framework which, as far as we are concerned, have been largely overlooked and not sufficiently studied. Moreover, their inclusion may be crucial to overcome the misspecification issue, which has been previously highlighted as one of the major causes of disparity in final estimations (Stern, 2004, 2010). In addition to this, the omission of spatially lagged variables when they are relevant for the data generating process will lead to biased estimates (LeSage and Pace,

* Corresponding author. Present Address: Department of Economics, University of Oviedo, Avda. Del Cristo, s/n., Oviedo 33071, Asturias, Spain.
E-mail addresses: UO217340@uniovi.es (R. Balado-Naves), jbanos@uniovi.es (J.F. Baños-Pino), mmayorf@uniovi.es (M. Mayor).

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2009), which may explain why many studies on CO_2 emissions have found extremely high and out of sample turning points (e.g., Holtz-Eakin and Selden, 1995; Galeotti and Lanza, 1999).

According to the foregoing, the question is how spatial models may contribute to estimate the impact of globalisation on the EKC. In this sense, trade profits are heavily influenced by distance costs (e.g., Hummels, 1999; Nitsch, 2000; Head and Mayer, 2002; Berthelon and Freund, 2008), thus one might suggest that international relationships are prone to be clustered around certain areas as long as trade and communication costs are sensitive to distance. In this regard, Beckerman (1956) states that developing countries are highly dependent on means of transport. Thus, as they close the distance between themselves and more-developed and important economies, their potential growth increases. Moreover, less-developed countries tend to generate a higher trade concentration than developed ones.

Given that distance is important for trade, the inclusion of spatial relationships allows us to test the pollution haven hypothesis (PHH) using new methodologies, as well as the existence of technological spillovers increasing energy efficiency. The PHH proposes that richer countries might present decreasing growth rates of pollution due to their export of environmentally harmful productive processes to poorer economies, leading to a situation where global net emissions do not decrease (Cole, 2004). Previous studies have tested the PHH for CO_2 emissions relying only on the statistical significance of explanatory variables reflecting trade (trade openness, imports from developing countries, exports to developing countries), which did not account for pollution transfers among countries in the same state of development (Cole, 2004; Kearsley and Riddel, 2010). In this sense, we propose to overcome this shortcoming by considering spatial econometric models.

In contrast to previous spatial studies, which have mainly focused on the policy mimicry of environmental standards using spatial lags on the dependent variable, we study how neighbouring per capita income and other explanatory variables, such as energy intensity, can impact national per capita CO_2 emissions. To this end, we estimate two types of EKC: a standard type, augmented by the share of renewable energy consumption over total energy consumption, the value added of the services sector over GDP and the energy intensity; and a "spatial EKC" (SEKC), which extends the previous one by using both spatially lagged per capita income and energy intensity.

The remainder of the paper is organised as follows. Section 2 contains a brief literature review for the EKC and its spatial approach. Section 3 describes both augmented and spatial EKC that will be estimated. Section 4 describes the data used in the empirical part of the paper. Section 5 presents the estimated models and discusses their results. Section 6 shows several forecasts for the EKC and SEKC. Section 7 presents conclusions and policy implications.

2. Literature review

The origins of the "Kuznets-like" analysis for environmental quality can be traced back to the study of NAFTA's effects on certain pollutant concentrations (Grossman and Krueger, 1991) and the World Bank report about the effects of economic development on the environment (IBRD, 1992). The pioneering works of Grossman and Krueger (1991, 1994) considered the idea that expanding economies might not always lead to greater environmental harm. The central thrust is that increasing trade may create new opportunities for environmentally friendly sectors (*composition effect*), as well as boost greener technical progress and productive efficiency (*technique effect*). Both effects should compensate, or even overcome, the impact of economic growth on pollution (*scale effect*). Nevertheless, it must be also highlighted that trade based on differences in production costs can account for migration of pollution from developed to developing countries, provided that in these latter there is a less stringent environmental regulation. Therefore, some sort of pollution displacement might occur between these types of countries (the pollution haven hypothesis), leading to a situation where global net pollution does not decrease. Despite this event might be crucial for understanding the evolution of global CO_2 emissions, we have found few studies that have directly considered it. Additionally, none of them have taken into account how geographical space, and therefore spatial processes, may play a major role in pollution transfers. In this sense, we follow the hypothesis expressed by Wang et al. (2013) that not only "all the subjects that are related to environmental issues are inherently spatial" but there also exist spatial interactions between countries due to trade or technological diffusion.

The first category of empirical studies of EKC for CO_2 was principally focused on the per capita income impact on per capita emissions, without taking into account other explanatory variables rather than national traits or time trends. Therefore, the 1990–2000's framework revolved around panel data estimations considering fixed effects for large sets of countries. Almost all these studies agree on the non-existence of an inverted U-shaped curve due to the excessive size of the estimated turning points (Shafik, 1994; Holtz-Eakin and Selden, 1995; Roberts and Grimes, 1997; Galeotti and Lanza, 1999), the finding of a monotonically increasing relationship (De Bruyn et al., 1998), the consideration of nonlinear dynamics as the major driver of polluting behaviours (Moomaw and Unruh, 1997) or the existence of heterogeneity in the estimated coefficients among countries (Dijkgraaf, Vollebergh, 1998). Some of them argued that the most developed countries were coming closer to a less steep trend of per capita emissions beyond a certain level of wealth rather than an inverted U-shape curve.

In essence, these preliminary works presented an important absence of explanatory capacity due to their focus on per capita income levels. As Moomaw and Unruh (1997) asserted, these initial results seemed to be more a by-product of the specification than a reflection of reality. These authors stressed the importance of market shocks in the long-term reduction of CO_2 emissions, pointing out that the EKC in its initial reduced form is not a fair representation of structural changes. In this sense, Schmalensee et al. (1998) argued that there might be a misspecification problem. More precisely, the inclusion of explanatory variables reflecting shifts in the industrial composition or changes in environmental policy would better explain differences in pollution among industrialised and developing countries. In addition, De Bruyn et al. (1998) also pointed out the weakness of reduced forms for policy implications.

In order to overcome this misspecification problem, the second category of carbon-dioxide-EKC studies started to consider new explanatory variables on the basis of a deeper theoretical background and the reassessment of previously posed hypotheses. Nevertheless, the misleading results derived from the juxtaposition of countries in different development stages and the existence of heterogeneity among the estimated coefficients for every country (Dijkgraaf, Vollebergh, 1998), led to the study of time series instead of cross section or panel data. In this regard, the use of Error Correction models and autoregressive models became more popular in the carbon-dioxide-EKC framework for the late 1990's to the mid-2000's (Lim, 1997; Panayotou et al., 2000; Egli, 2002; Pauli, 2003; Friedl and Getzner, 2003; Cole, 2004).

A large part of these second-group studies tested the existence of the PHH by including some sort of trade-reflection variable (Panayotou et al., 2000; Egli, 2002; Friedl and Getzner, 2003; Cole, 2004). There was no consensus about the final results. However, most of them pointed towards the non-existence of this phenomenon, or at least, that it was not required to achieve a bell-shaped relationship. We stand out the comprehensive analysis carried out by Cole (2004) about the PHH. This study employed trade-paired data for the US, the UK and Japan in relation to their main undeveloped foreign markets and its results did not support the PHH for CO_2 emissions. Nevertheless, the lack of a more representative sample for the industrialised world should be taken into account when interpreting its final results.

The other major focus of this second group was to test how

structural changes may help to the EKC emergence (Panayotou et al., 2000; Friedl and Getzner, 2003; Cole, 2004). Again, estimations led to a stalemate in this matter. However, this may be a result derived from the quality of the explanatory variables used to capture this effect. Whilst in Panayotou et al. (2000) capital intensity is employed to test the structural change hypothesis, obtaining strong evidences of its existence, Friedl and Getzner (2003) include the share of the services sector over total GDP and find that it is very close to the statistical non-significance. Finally, Azomahou et al. (2006) rejected the structural change and EKC hypotheses using kernel regression methods.

A third category of studies was divided among those who used Autoregressive Distributed Lag (ARDL) models (e.g. Coondoo and Dinda, 2008; Halicioglu, 2009 or Narayan and Narayan, 2010), and those who continued testing complementary hypotheses to the EKC using traditional panel data or time series estimations (e.g. Kearsley and Riddel, 2010; Franklin and Ruth, 2012 or Zhang and Zhao, 2014).

On the whole, we may assert that the ARDL-cointegration studies do not achieve a unanimous result for the EKC hypothesis. For instance, Coondoo and Dinda (2008) analysed the impact of inter-country wealth inequalities on the income-pollution relationship, finding support only for the EKC in Europe. Halicioglu (2009) did not find strong evidence for the EKC in Turkey as well as an innocuous impact of trade openness on the evolution of carbon dioxide emissions. In this sense, Jalil and Mahmud (2009) also found that trade openness did not impact on Chinese emissions, but the EKC hypothesis was not rejected. For the European Union, Acaravci and Ozturk (2010) solely found a bell-shaped curve in Italy and Denmark.

Another set of ARDL-cointegration studies considered new explanatory variables, such as energy intensity and energy composition (Iwata et al., 2011; Baek and Kim, 2013; Bölük and Mert, 2014, 2015; Baek, 2015; Al-Mulali et al., 2016). In brief, their results were mixed, even though they found a positive impact of both nuclear and renewable energies on environmental sustainability. Additionally, Ertugrul et al. (2016) detected evidence of the existence of the PHH in Turkey, India, China and Indonesia. Besides, Lægreid and Povitkina (2018) estimated the impact of political institutions on carbon dioxide emissions for 154 countries, finding partial support to the EKC.

Among the standard panel data or time series estimations, some of them stand out due to their ground-breaking contributions to the CO_2 EKC framework. To mention some examples, Kearsley and Riddel (2010) performed an extensive reanalysis of the PHH for several pollutants, taking also into consideration the structural change hypothesis. Their main results pointed towards a positive and monotonous relationship between income and carbon dioxide emissions due to the large sized turning points. As in Cole (2004), they did not find strong support for the existence of the PHH but rather the opposite outcome. Other researchers studied the impact of income inequality and structural changes on carbon dioxide emissions using long time series for the US (Franklin and Ruth, 2012) and panel data for Chinese provinces (Zhang and Zhao, 2014), finding opposite results in relation to their inclusion.

In summary, these previous studies have largely ignored the presence of spatial relationships, which indeed may be linked to the original idea of Grossman and Krueger (1991, 1994) of trade relationships changing pollution patterns among countries. As Wang et al. (2013) and Kang et al. (2016) asserted, spatial interactions may be a reflection of global integration processes, manifested in commerce, technological diffusion or capital inflows. In this sense, Rupasingha et al. (2004) were the first to consider spatial spillovers in the EKC framework. Subsequently, Maddison (2006) also analysed emissions of several pollutants employing three spatial models: the SLM (Spatial Lag Model), the SLX[1] (Spatial Lag of X) and the SEM (Spatial Error Model). Their results pointed towards the existence of spatial autocorrelation, in the form of policy mimicry and neighbouring income influences on national emissions.

To the best of our knowledge, the explicitly inclusion of spatial interactions in the analysis of the relationship between CO_2 emissions and income has been mainly focused on China (Auffhammer and Carson, 2008; Chuai et al., 2012; Kang et al., 2016; Wang and Ye, 2016). Whilst none of these studies supported the EKC hypothesis, they detected statistically significant spatial autocorrelation among Chinese provinces.

A common element that must be pointed out from previous spatial EKC studies is the dominance of SLM and SEM estimations, leading to results that can barely be interpreted or used for policy making. Following the actual strand in the spatial econometric literature we will focus on the SLX and the Spatial Durbin Error (SDEM) models, which are suitable for testing the PHH and the existence of technology spillovers. The explicit consideration of spatial interactions through spatially lagged explanatory variables allows us to analyse influences among neighbouring countries. This will enable us to test whether some sort of indirect EKC exists, which may lead to a lower national turning point.

3. The EKC and the spatial econometrics

3.1. The standard EKC

As mentioned above, many studies have employed several approaches to test the EKC hypothesis. However, we decided to estimate a log-linear EKC where we try to include the main drivers for CO_2 emissions:

$$\ln e_{it} = \alpha_i + \gamma_t + \beta_1 \ln y_{it} + \beta_2 (\ln y_{it})^2 + \beta_3 RE_{it} + \beta_4 SVC_{it} + \beta_5 \ln EI_{it} + \varepsilon_{it} \tag{1}$$

where e_{it} is the per capita CO_2 emissions; y_{it} is the per capita income; RE_{it} is the share of renewable energy consumption in total final energy consumption; SVC_{it} is the value added of the services sector over GDP; and EI_{it} represents the energy intensity, which can be understood as a proxy for technological progress. *ln* stands for logarithms, α_i represents individual fixed effects, γ_t is the time fixed effects and ε_{it} represents the error term. This equation tries to reflect the four major drivers of pollution dynamics (Grossman and Krueger, 1991, 1994; Stern, 2004; Dinda, 2004; Kaika and Zervas, 2013a): the scale effect and the income elasticity of environmental quality demand ($ln y_{it}$ and $ln y_{it}^2$), the composition effect (RE_{it} and SVC_{it}) and the technological effect ($lnEI_{it}$). We do not include a cubic term for income because an N-shaped curve would prove to be more a result of data fitting to the polynomial function rather than a true image of reality (Moomaw and Unruh, 1997).[2]

The expected signs for the major drivers' coefficients are:

(I) $\beta_1 > 0$ and $\beta_2 < 0$

It is expected that an increase in per capita production will increase per capita emissions. Conversely, if we consider that the economic agent must choose between two relevant products (consumption goods vs. environmental quality), as income grows and the population starts to satisfy its basic needs, the marginal utility of consumption starts to fall, whereas the marginal utility of environmental quality rises. After a turning point is reached, per capita emissions will present a negative growth rate as per capita income increases.

(II) $\beta_3 < 0$

If economies change their input mix from non-renewable to renewable energies, it is expected that per capita emissions will be

[1] The author did not explicitly use this denomination in their paper. Indeed, spatial regression model is the selected name by the author.

[2] Moreover, the estimated turning points will present unreachable magnitudes, apart from the risk of obtaining imaginary roots.

reduced when a new good or service is produced. Richmond and Kaufmann (2006) find the inclusion of fuel consumption shares determinant for supporting the EKC and the size of the estimated turning points. In addition, measuring the impacts of the energy mix on CO_2 emissions will prove very useful for policymaking in the long-run.

(III) $\beta_4 < 0$

The dominant sector of an economy will also determine the amount of CO_2 generated by each unit of product. Historically, the first stages of development are based on the agricultural sector, where production generates only a small amount of pollution. As economies start to become industrialised, most of the production comes from the secondary sector, where manufacturing is highly polluting. Finally, the third stage of development will be based on services, which are supposedly less polluting.

(IV) $\beta_5 > 0$

As economies boost their technological progress, their productive processes become more efficient and cleaner. This means that industries will require smaller amounts of polluting energy to make a new unit of output. We use the amount of energy used per unit of GDP as a proxy for energy efficiency.

3.2. The spatial EKC

As mentioned in Section 2, the standard EKC hypothesis for CO_2 emissions has been studied using different methodologies and samples, leading to inconclusive results. According to Dinda (2004) and Stern (2004), the omission of relevant variables may explain this disparity of results. Thus, considering spatial relationships may help solve the issue of omitted relevant variables.

Perrings and Hannon (2001) state that the relationship between economic growth and pollution depends on the timing and location of the environmental effects. Therefore, the geographic distance between CO_2 emitters and regions where climate change has greater impacts, might determine the formation of polluting clusters. Observing the average per capita CO_2 emissions in 173 countries, for the 1990–2014 period, it is possible to observe a World that, in terms of pollution is roughly divided between the Northern and the Southern Hemispheres (Fig. 1). Most of the Northern countries and Oceania present emissions of more than 6 t per capita (e.g., the US, Canada, Europe, Russia, the Arabian Peninsula). The more environmentally friendly Southern Hemisphere, including Southern Africa, South America and South-eastern Asia, presents emissions lower than 2 t per capita. More-homogeneous clusters can be found on a smaller scale, such as for Canada-US, the former Soviet Union, the Hindustan Peninsula, and Sub-Saharan Africa.

Source: Data from World Development Indicators, The World Bank. Prepared by the authors.

Supposing that spatial relationships exist for CO_2 emissions, the correct spatial specification must be selected. According to Halleck Vega and Elhorst (2015), seven spatial models have been considered in the literature that differ according to whether spatial spillovers are global or local. LeSage (2014) states that the existence of endogeneity in the spatial relationships will determine the type of spatial spillover. The local effects are purely exogenous, which means that changes in neighbouring explanatory variables will directly impact the national dependent variable. By contrast, when endogenous spatial effects exist, a feedback effect will arise. This feedback effect means that changes in one nation will impact neighbouring countries, and these will subsequently transfer part of the impact to their neighbours, and so on. Finally, these changes will return to the national dependent variable. Thus, the relevant issue is to detect what type of spatial spillover effect is arising from the relationship between the environment and economic growth.

Maddison (2006, 2007) argues that the PHH could be a type of local spillover. Moreover, if technology is related to trade -and therefore to distance- clean technology diffusion may also be measured as a local spillover. Reppelin-Hill (1999) found that the adoption of cleaner technology in the steel industry may be distorted by trade openness. For global spillovers, Maddison (2006) suggests that the competition among governments in terms of capital or trade attraction will lead to changes in the environmental policy. Moreover, he states that

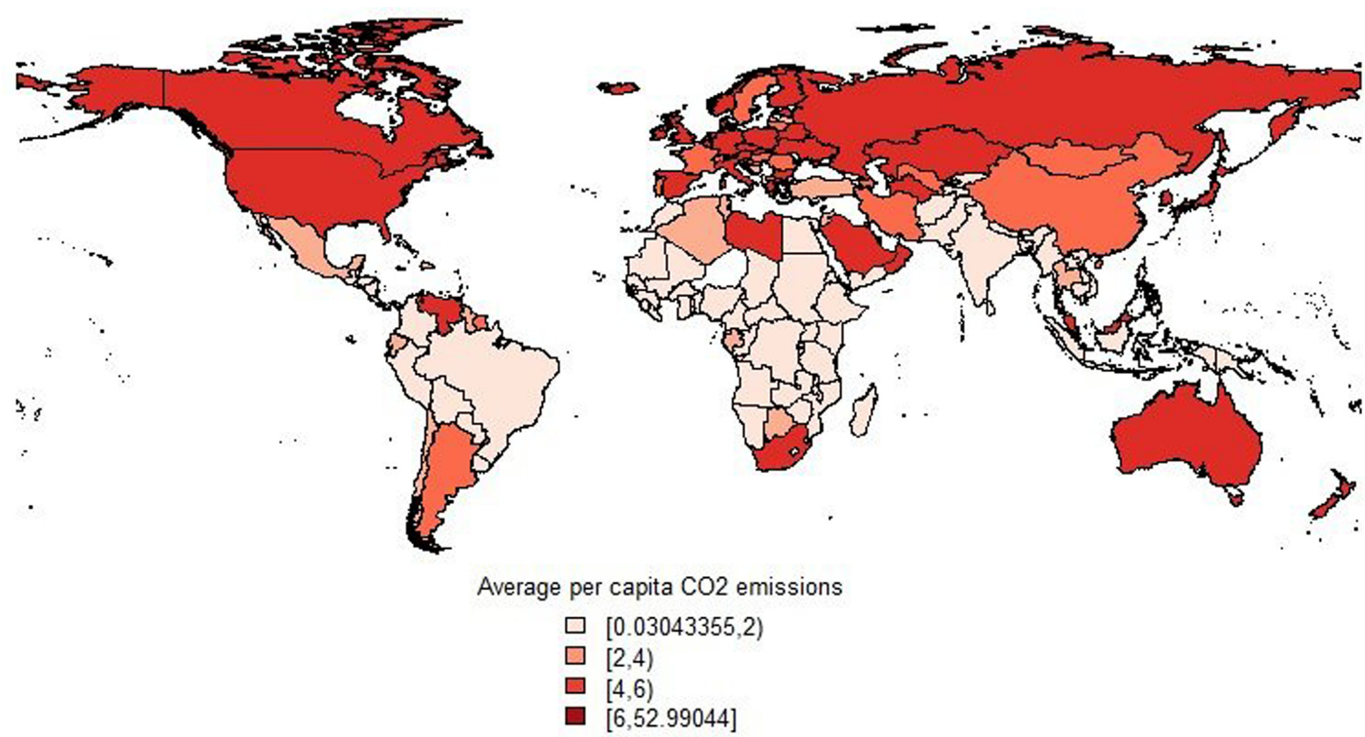

Fig. 1. CO_2 emissions (tonnes per capita) in the World. (1990–2014).

"politicians constantly assess policy against those of their neighbours in order to legitimate their actions and to reduce the costs of decision-making, resulting in similar environmental standards". This policy mimicking can occur swiftly and at a global level due to the lower barriers to communication and travel (Shipan and Volden, 2012). Nevertheless, we will only focus on the local spillovers due to two major reasons: the significance of global spillovers may only be determined by the omission of other spatially lagged explanatory variables (Corrado and Fingleton, 2012); and imposing the condition that each country is affected by all other countries' emissions seems implausible for a global sample.

There are three spatial models which only account for exogenous spatial spillovers: the SDEM (Spatial Durbin Error Model), which includes spatial lags for the explanatory variables and the error term, and therefore nests the following models; the SLX (Spatial Lag of X), which only includes spatially lagged explanatory variables and whose estimated parameters should be unbiased despite the SDEM being the true model, since spatial dependence in the disturbances represents only an efficiency problem (LeSage, 2014); and the SEM (Spatial Error Model), which only takes the spatially lagged error term into consideration. We follow the stepwise backward elimination procedure as in Jiang et al. (2014) with the aim of choosing the explanatory variables, starting with the SDEM and testing whether it could be simplified to one of its nested models (SLX or SEM). This will allow us to compare which exogenous spatial model better fits the data in order to avoid the misspecification problems that commonly appear in EKC studies. Our final EKC regression will take the following form[3]:

$$\mathrm{lne}_{it} = \alpha_i + \gamma_t + \beta_1 \ln y_{it} + \beta_2(\ln y_{it})^2 + \beta_3 \mathrm{RE}_{it} + \beta_4 \mathrm{SVC}_{it} + \beta_5 \mathrm{lnEI}_{it} + \theta_1 \sum_{j=1}^{N} w_{ij} \ln y_{it} + \theta_2 \sum_{j=1}^{N} w_{ij} (\ln y_{it})^2 + \theta_3 \sum_{j=1}^{N} w_{ij} \mathrm{lnEI}_{it} + \varepsilon_{it} \tag{2}$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^{N} \mathrm{w}_{ij} \varepsilon_{it} + v_{it}$$

where $\sum_{j=1}^{N} w_{ij} lny_{it}$ and $\sum_{j=1}^{N} w_{ij} (lny_{it})^2$ measure the exogenous interaction effects among per capita income of all the j neighbours to country i; $\sum_{j=1}^{N} w_{ij} lnEI_{it}$ the exogenous interaction effects among the energy intensity of all j neighbours to country i; θ_p the spillover effects for the p spatially lagged variables; $\sum_{j=1}^{N} w_{ij} \varepsilon_{it}$ the interaction effects among the disturbance terms of the different observations; and λ the strength of dependence between error terms. The expected signs for the new estimated coefficients are:

(I) $\theta_1 > 0$ and $\theta_2 < 0$ if the PHH is supported in the short-term.
It is expected that an increase in neighbouring per capita production will increase countries' trade and investment capacities. Then, national per capita emissions will rise via greater inflows of foreign polluting capital. A turning point will be reached when the neighbouring marginal benefit related to polluting capital exports is exceeded by the marginal cost of climate change. From this point onwards, inflows of foreign investment will shift from polluting to environmentally friendly capital.

(II) $\theta_1 > 0$ and $\theta_2 \geq 0$ if the PHH is supported in the long-term.
This is the same as above, except that national emissions will follow a positive trend adopting a slope that may become steeper as neighbouring per capita income grows. This will reflect a constant transfer of polluting capital between neighbouring countries at a constant rate (θ_2=0) or an increasing rate ($\theta_2 > 0$).

(III) $\theta_1 \leq 0$ and $\theta_2 \leq 0$ if the PHH is rejected.

(IV) $\theta_3 > 0$
The existence and relevance of technology spillovers have been proved by previous researchers (Branstetter, 2001; Coe et al., 2009). Moreover, distances reduce their impact (Bottazzi and Peri, 2003; Funke and Niebuhr, 2005). Therefore, we expect that as neighbouring energy efficiency is increased, national industries will mimic neighbouring productive processes to sustain international competitiveness. Consequently, national emissions will fall.

4. Database

We employ a panel data set composed of 173 countries[4] for the 1990–2014 period to analyse the existence of a spatial EKC for CO_2 emissions. All data belong to the World Bank Development Indicators Database. All variables (Table 1), except for the share of renewable energy in total final energy consumption and the value added of services over GDP, are transformed into logarithms for two reasons: firstly, because the final results will be interpreted in percentage terms for all variables (for the log-log estimations, there will be elasticities, while for the log-linear estimations, there will be semi-elasticities). Secondly, we want to avoid heteroskedasticity in the data.

In line with previous literature, we define neighbourhood relationships using the maximum distance observed between all pairs of closest neighbouring countries. The objective is to ensure one neighbour for each country (Maddison, 2006; Hao et al., 2016). The spatial weights matrix is created using the inverse distance between country centroids.

5. Results and discussion

In this section, we firstly perform the joint significance LR tests for all areas in order to select which fixed effect specification better fits the data. Subsequently, we estimate both standard and spatially lagged EKCs as well as study if the SDEM model can be reduced to the SLX. Finally, we compare and discuss the obtained results.

Table 2 shows the results of the LR tests for joint significance. For the 173 countries representing most of the World, Europe, South America and Africa, the null hypothesis of non-significant individual effects is rejected at a 5% significance level. The null hypothesis for time effects is not rejected, so their estimations will only include individual effects. In North America, Asia and Oceania, both hypotheses are rejected at the same significance level, so their estimations will include both individual and time fixed effects.

Table 3 presents the OLS estimations for the non-spatial EKC. At a 1% level of significance, all areas except for Oceania support the EKC hypothesis. In all cases, the estimated coefficient for the per capita income (*lny*) is positive and for the quadratic term ($(lny)^2$) is negative. The other explanatory variables, except for the relative weight of the services sector (*SVC*), seem to present robustness in their results for the regions analysed.

The relative consumption of renewable energy (*RE*) and energy intensity (*lnEI*) are significant at a 1% level for all estimates. Moreover, their estimated signs are constant among the areas, negative for the first one and positive for the second one. These results coincide with our expectations. As economies shift their energy consumption from non-renewable and polluting sources to renewable sources, per capita CO_2 emissions will decrease. The energy intensity reflects the inefficiency of productive processes in terms of energy use, so reductions in the energy employed per unit of good and service produced will reduce the emissions. On the other hand, the output composition (*SVC*), measured as the degree of tertiarisation, is not significant for explaining changes in per capita CO_2 emissions in the areas of North America, South

[3] We have not spatially lagged RE_{it} in order to avoid double accounting (it measures final consumption, then it already considers imported energy). Regarding to SVC_{it}, we do not expect that neighbouring output composition will be relevant for national carbon emissions. Moreover, we tested the significance of both coefficients for the world as a whole, leading to statistical rejection at a 5% level of significance.

[4] See Appendix A for sample statistics. Appendix B presents a list of countries.

Table 1
Dependent and explanatory variables.
Source: Data from World Development Indicators, The World Bank. Prepared by the authors

	Description
e	Per capita carbon dioxide emissions (tonnes of CO_2)
y	Per capita GDP, in purchasing parity power (constant 2011 international US$)
POP	Total population. All residents regardless of legal status or citizenship.
RE	Share of renewable energy in total final energy consumption. (%)
SVC	Value added of services over GDP (ISIC divisions 50–99) (%)
EI	Energy intensity level of primary energy (MJ/$2011 PPP GDP)

Table 2
LR-tests for joint significance.
Source: Prepared by the authors.

Area/degrees of freedom (indiv. FE)	LR-test joint significance individual fixed effects	LR-test joint significance time fixed effects
World/173	6810.964*** (p = 0.000)	36.790* (p = 0.060)
Europe/36	1893.534***(p = 0.000)	24.203 (p = 0.507)
North America/22	688.721***(p = 0.000)	76.070*** (p = 0.000)
South America/12	441.913*** (p = 0.000)	15.885 (p = 0.918)
Asia/44	1387.917***(p = 0.000)	45.793*** (p = 0.006)
Oceania/10	333.161*** (p = 0.000)	144.115*** (p = 0.000)
Africa/49	1961.127*** (p = 0.000)	31.789 (p = 0.164)

Notes: The degrees of freedom for the LR time effect tests are equal to 25 in all cases. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.

America and Asia. To conclude the standard EKC analysis, the estimated turning points in all areas, except for Asia, are extremely high, similar to what occurred in previous studies. No country in the sample reaches or even comes close to the estimated point for the World as a whole. Hence, we will focus on the spatial EKC results, expecting that its estimates will shed more light on the underlying dynamics of income and pollution.

As noted in Section 3, we decided to use both SDEM and SLX specifications because they are the only spatial models which allow us to model local spatial spillovers (LeSage, 2014; Halleck Vega and Elhorst, 2015). In addition, the spatial EKC will allow us to test the existence of the PHH and technological spillovers. If the PHH is supported, then three turning points (y^*) will be estimated: the direct turning point, which is estimated only taking into account the national income elasticity ($y_D^* = -\frac{\beta_1}{2\beta_2}$), as it was carried out using the non-spatial EKC; the indirect turning point, which is estimated by only taking into account the changes in neighbouring per capita income ($y_I^* = -\frac{\theta_1}{2\theta_2}$); and the total turning point, which is obtained by considering both national and neighbouring changes ($y_T^* = -\frac{(\beta_1+\theta_1)}{2(\beta_2+\theta_2)}$).

Table 4 presents the spatial EKC estimations for both SDEM and SLX models. First of all, we study the LR tests in order to determine whether the SDEM can be reduced to a nested form. The LR SLX test poses a null hypothesis where the spatial lag of the error term (λ) is equal to zero, which is clearly not rejected in all areas; whilst the LR SEM test poses a null hypothesis where the spatial lag of all the explanatory variables (θ_p) is equal to zero, which is clearly rejected for the world as whole and almost all areas. Therefore, we will focus our discussion on the SLX results. Starting with the national income elasticity to per capita CO_2 emissions (*lny* and *(lny)²*), in all cases except for Oceania, the EKC hypothesis is supported again at a 1% significance level. Comparing both standard and spatial regressions, the differences in size of the estimated coefficients are small. Moreover, their signs and statistical

Table 3
Non-spatial estimations for logarithmic per capita CO_2 emissions.
Source: Prepared by the authors.

Determinants	**World (Individual FE)**	**Europe (Individual FE)**	**North America (Two-Way FE)**	**South America (Individual FE)**	**Asia (Two-Way FE)**	**Oceania (Two-Way FE)**	**Africa (Individual FE)**
N	173	36	22	12	44	10	49
lny	2.607***(30.159)	2.152***(17.297)	1.918***(7.847)	2.332***(3.931)	3.081***(18.842)	0.894***(3.960)	1.895***(8.481)
$(lny)^2$	− 0.095***(− 19.841)	− 0.070***(− 10.500)	− 0.057***(− 4.457)	− 0.074** (− 2.315)	− 0.123***(− 13.393)	− 0.019 (− 1.506)	− 0.057***(− 4.360)
RE	− 0.014***(− 33.231)	− 0.014***(− 21.696)	− 0.010***(− 19.937)	− 0.009***(− 6.361)	− 0.007***(− 7.645)	− 0.016***(− 30.555)	− 0.016***(− 15.825)
SVC	− 0.002***(− 4.167)	− 0.004***(− 6.534)	0.000 (− 0.185)	0.000 (− 0.022)	0.001 (1.355)	− 0.002** (− 2.138)	− 0.005***(− 4.614)
lnEI	0.710***(45.667)	0.773***(32.324)	0.965***(49.976)	1.029***(20.179)	0.821***(28.768)	0.843***(34.815)	0.459***(11.723)
R^2 (Adjusted)	0.698	0.772	0.882	0.803	0.656	0.898	0.659
σ^2	0.024	0.006	0.002	0.006	0.027	0.002	0.047
lnL	1877.5	1006	834.229	341.2782	412.724	420.122	137.072
Durbin-Watson	1.943	1.868	2.223	2.015	2.118	2.155	1.839
Turning Point (US$)	926,226.9	5,137,116.408	18,038,762.24	7,463,721.176	270,026.7	10,521,646,923	15,033,135.4

Notes: lny, RE, SVC and lnEI are the logarithms of per capita GDP, renewable energy consumption over the total energy consumption, weight of the tertiary sector over the GDP and the logarithm of energy intensity. The t statistics for the estimated coefficients are in parenthesis. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.

Table 4
Spatial estimations for logarithmic per capita CO_2 emissions.
Source: Prepared by the authors.

Determ	World (Individual FE)		Europe (Individual FE)		North America (Two-Way FE)		South America (Individual FE)	
	SLX	SDEM	SLX	SDEM	SLX	SDEM	SLX	SDEM
lny	2.448***(26.086)	2.442***(25.697)	1.593***(10.036)	1.566***(9.777)	2.058***(7.461)	2.106***(7.245)	3.119***(4.976)	3.102***(4.904)
(lny)^2	− 0.086***(−16.167)	− 0.086***(−15.911)	− 0.035***(−3.812)	− 0.033***(−3.595)	− 0.065***(−4.455)	− 0.067***(−4.388)	− 0.121***(−3.523)	− 0.120***(−3.464)
RE	− 0.013***(−30.500)	− 0.013***(−29.952)	− 0.012***(−16.815)	− 0.012***(−16.692)	− 0.010***(−19.751)	− 0.011***(−19.341)	− 0.007***(−4.873)	− 0.007***(−4.938)
SVC	− 0.002***(−4.126)	− 0.002***(−4.101)	− 0.002***(−3.230)	− 0.002***(−3.072)	0.000 (−0.275)	− 0.001 (−0.163)	0.000 (−0.050)	− 0.001 (−0.131)
lnEI	0.702***(44.614)	0.701***(43.896)	0.785***(33.226)	0.784***(32.675)	0.968***(46.164)	0.969***(44.145)	1.012***(19.972)	1.011***(19.784)
Wlny	0.960***(5.088)	0.979***(4.942)	0.995***(3.118)	1.033***(3.065)	− 0.541 (−1.198)	− 0.763*(−1.716)	− 0.673 (−1.047)	− 0.718 (–1.111)
W(lny)^2	− 0.049***(−4.610)	− 0.051** (−4.523)	− 0.045***(−2.679)	− 0.047***(−2.654)	0.026 (1.116)	0.037 (1.610)	0.047 (1.305)	0.049 (1.362)
WlnEI	0.108***(2.615)	0.097** (2.216)	0.351***(5.606)	0.359***(5.403)	0.008 (0.194)	0.020 (0.523)	0.188***(3.106)	0.184***(3.007)
Wu		0.075** (2.299)		0.085 (1.196)		− 0.088 (−1.373)		− 0.023 (−0.416)
R^2 (Adj.)	0.701	0.701	0.785	0.786	0.882	0.883	0.810	0.815
σ^2	0.024	0.025	0.006	0.006	0.003	0.003	0.006	0.006
lnL	1893.7	1894.244	1031.900	1032.154	835.053	837.676	347.809	347.769
DW	1.932		1.886		2.212		1.969	
LR SLX		1.403		0.4780		5.247		− 0.080
		(p = 0.924)		(p = 0.993)		(p = 0.387)		(p = 0.999)
LR SEM		30.002***		52.922***		3.412		12.178**
		(p = 0.001)		(p = 0.001)		(p = 0.637)		(p = 0.032)

Determ	Asia (Two-Way FE)		Oceania (Two-Way FE)		Africa (Individual FE)	
	SLX	SDEM	SLX	SDEM	SLX	SDEM
lny	2.707***(15.617)	2.698***(15.257)	0.815***(3.492)	0.794***(3.259)	1.797***(7.953)	1.786***(7.761)
(lny)^2	− 0.108***(−11.247)	− 0.107***(−10.972)	− 0.012 (−0.927)	− 0.011 (−0.806)	− 0.051***(−3.817)	− 0.050***(−3.693)
RE	− 0.007***(−6.977)	− 0.007***(−6.891)	− 0.016***(−29.095)	− 0.016***(−27.311)	− 0.017***(−15.849)	− 0.017***(−15.511)
SVC	0.000 (0.426)	0.001 (0.607)	− 0.001*(−1.659)	− 0.001*(−1.712)	− 0.006***(−4.910)	− 0.006***(−4.858)
lnEI	0.826***(29.530)	0.823***(28.746)	0.857***(35.103)	0.856***(33.430)	0.492***(12.406)	0.492***(12.189)
Wlny	1.089***(4.203)	1.109***(4.121)	− 1.762** (−2.227)	− 1.720** (−2.058)	0.121 (0.204)	0.087 (0.143)
W(lny)^2	− 0.042***(−2.916)	− 0.044***(−2.926)	0.121** (2.389)	0.118** (2.201)	− 0.023 (−0.691)	− 0.021 (−0.618)
WlnEI	0.056 (1.145)	0.057 (1.107)	0.060 (1.647)	0.064*(1.659)	− 0.363***(−3.413)	− 0.373***(−3.412)
Wu		0.085** (2.372)		0.055 (0.827)		0.032 (0.673)
R^2 (Adj.)	0.673	0.675	0.901	0.903	0.665	0.667
σ^2	0.026	0.028	0.002	0.002	0.046	0.048
lnL	441.244	442.173	424.630	425.012	148.560	148.236
DW	2.011		2.142		1.852	
LR SLX		1.858		0.762		− 0.647
		(p = 0.868)		(p = 0.979)		(p = 0.999)
LR SEM		52.705***		8.579		23.108
		(p = 0.001)		(p = 0.127)		(p = 0.001)

Turning P. (Direct)	1427.410	7860,786.1	7918.663	402.125	283.740	161,329 × 10^6	49,849.999
Turning P. (Indir.)	17.587	64.849	36.125	1.328	398.480	1.448	0.013
Turning P. (Total)	290.259	10,893.476	279,656.175	14,893.450	312.202	0.078	441.493

Notes: Same as in Table 3. W is the spatial weights matrix. We only show the estimated turning points for the SLX, expressed in constant 2011 international US$, thousands.

significance remain unaltered. Only North America and South America present increases in the non-squared term (from 1.918% to 2.058%, and 2.332–3.119%, respectively) and decreases in the squared terms (-0.057% to −0.065%, and −0.074% to −0.121%, respectively), whilst the remaining areas show the opposite change. Obviously, these changes have impacted the estimated direct turning points. The North and South American cases present reductions in their turning points (their sizes are reduced by 56% and 94%, respectively), whilst the other areas show increases ranging from 5% (Asia) to 1,533,209% (Oceania) compared to the non-spatial estimation.

Focusing on the magnitude of the coefficients, Oceania presents the lowest national income elasticity (0.815%), but the non-significance of the squared term seems to indicate that emissions will increase monotonically as income increases. South America presents the most responsive per capita CO_2 emissions to changes in national income (3.119%, regardless of the squared term), closely followed by Asia (2.707%). Even though South America's direct turning point (402,125.361 US$) is more feasible than that estimated for Oceania, the richest South American country is still too far away from it (Chile, with 22,226.452 US$ in 2014, represents roughly 5% of the direct turning point). In the Asian case, Macau (130,750.166 US$) and Qatar (120,860.068 US$) presented the closest per capita incomes in the year 2014, representing less than 47% of the Asian direct turning point (283,740.932 US$). Finally, the World as a whole presents the third highest income elasticity (2.448%, regardless of the squared term), although the direct turning point seems to be more unreachable compared to the South American and Asian cases.

The national coefficients for renewable energy consumption (*RE*) and energy intensity (*lnEI*) are statistically significant, and their signs remain identical to the non-spatial estimation. As in previous research, increases in renewable energy consumption will improve environmental quality (Marrero, 2010; Ben Jebli, Ben Youssef, 2015), and its inclusion may support the existence of the EKC (Sulaiman et al., 2013; López-Menéndez et al., 2014; Bölük and Mert, 2015). Nevertheless, an increase of 1% in the share of renewable energy will reduce per capita CO_2 emissions by barely −0.007% in the worst case (South America and Asia) to −0.017% in the best case (Africa). On the other hand, increases in energy intensity worsen environmental quality, which agrees with the results of previous research (Cole and Neumayer, 2004; Poumanyvong and Kaneko, 2010; Du et al., 2012; Liu et al., 2015; Wang et al., 2017). The estimated elasticity is very close to 1% in most areas, which emphasises the importance of energy efficiency in reducing carbon dioxide emissions. Notwithstanding, we cannot conclude that the value added of services over GDP (*SVC*) is relevant for explaining changes in emissions. As revealed in the non-spatial estimations, the degree of tertiarisation in North America, South America, and Asia is not statistically significant. Furthermore, in those areas where it is indeed significant, the estimated magnitude is quite close to 0%. Previous studies have found differing conclusions with respect to the impact of output structural changes on pollution. Lindmark (2002) find that services are not significant for explaining changes in Swedish CO_2 emissions. Moreover, Kaika and Zervas (2013b) have pointed out how the use of value-added data may give a false impression of changes in real GDP composition due to changes in prices.

Table 4 also presents the estimations for neighbouring per capita income and energy intensity (*Wlny*, $W(lny)^2$ and *WlnEI*). The World as a whole, Europe, Asia and Oceania support the existence of an indirect EKC at a 5% level of significance, i.e., the neighbouring per capita income apparently impacts national per capita emissions, probably through polluting capital transfers. However, the PHH is supported in different ways among these four geographical areas. Oceania presents a U-shaped curve for the indirect EKC. This means that as Oceanian countries become richer in the first stages of development, they will reduce neighbouring per capita emissions at a decreasing rate until a turning point equal to 1448.936 US$ is reached. However, the minimum value in the Oceanian sample is 1466.336 US$ (see Appendix A), which corresponds to the Solomon Islands and exceeds the estimated point. Therefore, further economic growth of Oceanian countries will increase neighbouring per capita CO_2 emissions at a growing rate. This seems to support the existence of a long-term PHH in Oceania. The remaining three areas that support the indirect EKC show a short-term dynamic on pollution displacement. Then, as their economies grow, the polluting capital could be displaced to neighbouring countries until a turning point is reached. This point can be explained by the marginal benefit of exporting polluting capital being exceeded by the marginal cost of neighbouring pollution (thus, we suppose that at some stage, individuals internalise the effects of neighbouring pollution). From this point onwards, populations from richer countries will start to import goods based on low-carbon processes and will export more environmentally friendly capital and carbon sequestration goods at increasing rates. In these three areas, the neighbouring income elasticity of national per capita CO_2 emissions is approximately 1%, regardless of the squared term.

The existence of technological spillovers (*WlnEI*) is supported in Europe, South America, Africa and the World as a whole. It seems remarkable that only Africa shows a negative estimated coefficient (-0.363%). This means that as African countries improve their productive processes in terms of energy efficiency (lower *lnEI*), their neighbours become more inefficient. Therefore, one could say that African countries may be following a spiral of diffusion of non-environmentally friendly technologies. Nevertheless, the total impact (that is, the addition of the average direct impact to the average indirect impact, equal to 0.129%) presents a positive influence, so national efforts are more influential than neighbouring changes for energy efficiency, therefore leading to decreases in national emissions. For the other areas, technological diffusion must be boosted in order to accelerate environmental improvements. Specifically, European countries show the largest indirect impact for technology spillovers (0.351%), probably due to the existence of an integration process and due to the relatively small size of the European states compared with other continents.

In summary, there seems to exist strong support for the direct EKC for both standard and spatial specifications in all areas except Oceania. In addition, there seems to only be a robust indirect EKC for the World as a whole, Europe and Asia, probably due to the way in which the spatial matrices have been specified. Nevertheless, the inclusion of spatially lagged variables does not seem to disrupt the standard estimates, but the estimated total turning points certainly suffer important changes when neighbouring influence is considered. Specifically, the estimate for the World presents a significant reduction in its total turning point compared to the standard estimate (a decrease of more than 68%, from 926,226.9 US$ to 290,259.573 US$). However, the total turning point is still out of the sample (the closest countries to it were Macau, with 130,750.166 US$, and Qatar, with 120,860.068 US$, in 2014).

6. Emission forecasts

As previous researchers have noted, if estimated turning points are far from the data, the income elasticity of per capita carbon dioxide emissions may tend to zero instead of becoming negative as income grows (Holtz-Eakin and Selden, 1995; Kearsley and Riddel, 2010). Therefore, we perform several forecasts of annual CO_2 emissions from 2015 to 2100 in order to assess whether considering spillover impacts agrees with the aforementioned conclusion.

Two per capita GDP growth rates are estimated: the first follows Holtz-Eakin and Selden's (1995) method,[5] whilst the second considers the existence of a spatial process.[6] We also create a faster GDP growth

[5] $lny_{it+1} - lny_{it} = \alpha_i + 0.083965 lny_{it} - 0.004258 (lny_{it})^2$.

[6] $lny_{it+1} - lny_{it} = \alpha_i + 0.091364 lny_{it} - 0.005124 (lny_{it})^2 + 0.014467 \sum_{j=1}^{N} w_{ij} lny_{it}$.

Table 5
Global emissions forecasts. Annual CO_2 emissions (gigatons of carbon dioxide).
Source: Prepared by the authors.

Year	2015	2030	2045	2060	2075	2100
Standard EKC						
Base g_y	35.210	49.889	66.362	81.565	93.701	107.909
Base g_y (W)	35.883	51.825	70.231	88.325	104.243	125.199
Base g_y (W)/gRE= 1%, gEI = −1%	35.381	41.390	45.535	46.724	45.590	46.356
Base g_y (W)/gRE= 2.5%, gEI = −2.5%	33.555	19.322	12.530	12.312	13.296	14.910
Base g_y (W)/gRE= 5%, gEI = −5%	32.249	9.958	7.399	5.533	3.899	1.986
Faster g_y	35.968	53.558	73.839	92.949	108.533	127.124
Faster g_y (W)	36.011	54.603	76.793	99.121	118.958	144.750
Faster g_y (W)/gRE= 1%, gEI = −1%	35.508	43.608	49.797	52.478	52.164	54.055
Faster g_y (W)/gRE= 2.5%, gEI = −2.5%	33.675	20.359	13.735	13.895	15.294	17.425
Faster g_y (W)/gRE= 5%, gEI = −5%	32.364	10.502	8.110	6.235	4.475	2.315
Spatial EKC						
Base g_y	36.121	52.235	70.616	87.350	99.681	103.746
Base g_y (W)	36.172	52.660	72.544	90.275	103.679	113.909
Base g_y (W)/gRE= 1%, gEI = −1%	35.689	42.486	47.933	48.862	46.248	41.627
Base g_y (W)/gRE= 2.5%, gEI = −2.5%	33.755	19.182	12.500	11.800	12.107	11.901
Base g_y (W)/gRE= 5%, gEI = −5%	32.448	9.772	6.845	4.629	2.902	1.148
Faster g_y	36.258	55.163	77.328	97.756	112.726	116.250
Faster g_y (W)	36.309	56.386	80.453	103.319	120.798	136.532
Faster g_y (W)/gRE = 1%, gEI = −1%	35.825	45.497	53.215	56.337	55.136	53.987
Faster g_y (W)/gRE = 2.5%, gEI = −2.5%	33.883	20.527	13.907	13.761	14.539	15.179
Faster g_y (W)/gRE = 5%, gEI = −5%	32.571	10.495	7.646	5.417	3.512	1.492

Notes: gy is the estimated per capita GDP growth rate. gy (W) includes the spatially lagged per capita GDP. gRE and gEI are the exogenous growth rates for the share of renewable energy in total final energy consumption and energy intensity respectively. The faster rates are obtained by adding 0.005 to the base growth rates.

rate by adding 0.005 to the estimates and exogenous growth rates for the share of renewable energy consumption and energy intensity in order to assess their effectiveness. The share of the services sector over GDP will be kept constant over time at the same levels as 2014, and the population forecasts will correspond to the medium fertility variant of the "UN World Population Prospects: The 2017 Revision".

The results presented in Tables 5, 6 and Fig. 2 point towards rejecting the EKC hypothesis in the long term. Although global CO_2 emissions seem to grow at a decreasing rate between 2015 and 2100, only two forecasts based on economic growth reach a turning point before the end of the XXI century (base and faster g_y for the SEKC). These results coincide with the estimates of Section 5, where it was shown that the spatial EKC will reach an earlier turning point because the displacement of polluting industries cannot be held in the long

term. However, their turning points are reached in 2090 and 2089, respectively, which implies that the average global temperature would have already increased. According to Sachs (2015), approximately 46% of carbon dioxide emissions remain in the atmosphere, and of this 46%, each 7800 million tonnes of CO_2 creates 1 ppm (ppm) CO_2 concentration. In 2014, the atmospheric concentrations of CO_2 were close to

Table 6
Global concentrations forecasts. Annual CO_2 concentrations (ppm).
Source: Prepared by the authors.

Year	2015	2030	2045	2060	2075	2100
Standard EKC						
Base g_y	402.076	439.939	491.809	557.899	635.997	785.848
Base g_y (W)	402.116	441.128	495.562	566.359	652.173	822.795
Base g_y (W)/gRE= 1%, gEI = −1%	402.087	436.304	475.061	516.130	557.028	624.183
Base g_y (W)/gRE= 2.5%, gEI = −2.5%	401.979	424.187	437.620	448.260	459.611	480.471
Base g_y (W)/gRE= 5%, gEI = −5%	401.902	417.820	425.157	430.815	434.913	439.072
Faster g_y	402.121	441.940	498.812	573.382	663.219	838.516
Faster g_y (W)	402.124	442.402	501.014	579.617	676.872	873.194
Faster g_y (W)/gRE= 1%, gEI = −1%	402.094	437.392	479.101	524.700	571.116	648.836
Faster g_y (W)/gRE= 2.5%, gEI = −2.5%	401.986	424.832	439.275	451.135	464.088	488.320
Faster g_y (W)/gRE= 5%, gEI = −5%	401.909	418.245	426.147	432.443	437.108	441.921
Spatial EKC						
Base g_y	402.130	441.425	496.259	566.902	650.336	803.666
Base g_y (W)	402.133	441.479	497.359	570.006	656.587	819.028
Base g_y (W)/gRE= 1%, gEI = −1%	402.105	436.813	477.191	520.237	562.446	626.850
Base g_y (W)/gRE= 2.5%, gEI = −2.5%	401.991	424.072	437.450	447.814	458.418	476.223
Base g_y (W)/gRE= 5%, gEI = −5%	401.914	417.710	424.715	429.674	432.917	435.691
Faster g_y	402.138	442.774	501.943	580.319	674.299	847.567
Faster g_y (W)	402.141	443.319	504.417	586.685	686.776	878.853
Faster g_y (W)/gRE= 1%, gEI = −1%	402.113	438.400	482.546	531.483	580.972	660.950
Faster g_y (W)/gRE= 2.5%, gEI = −2.5%	401.998	424.982	439.588	451.488	464.048	486.075
Faster g_y (W)/gRE= 5%, gEI = −5%	401.921	418.327	426.014	431.719	435.576	439.035

Notes: Same as in Table 6.

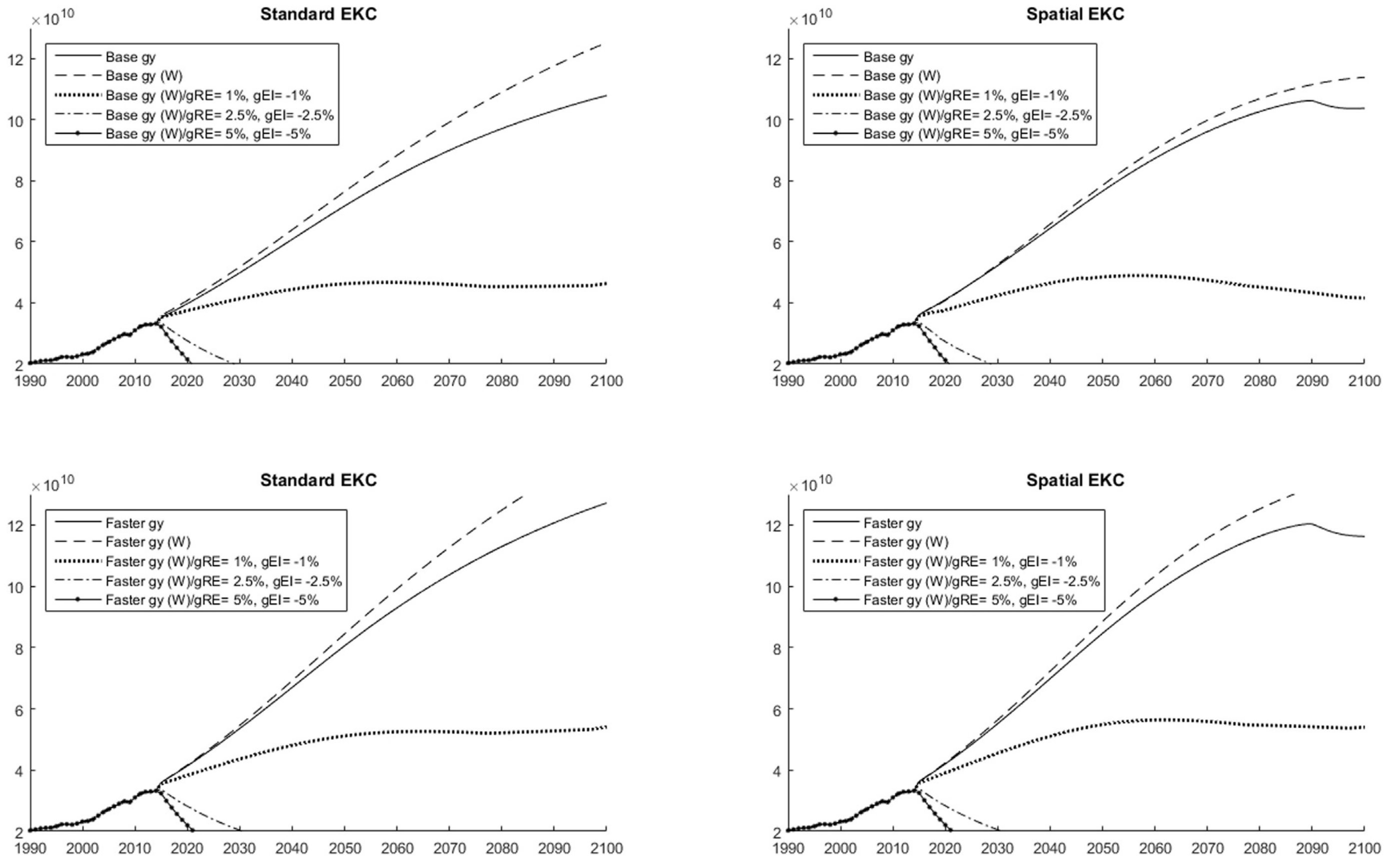

Fig. 2. Global emissions forecasts.

400 ppm; thus, for 2046, the CO_2 concentrations will exceed 500 ppm if we consider the base g_y for the spatial EKC. This implies a total increase in average global temperature of 2 °C since the nineteenth century. The conclusions for the remaining scenarios are similar or even worse (Table 6).

The only solution to accelerated climate change may be to invest in renewable energy and increase energy efficiency. Specifically, when we impose a growth rate of renewable energy consumption over total energy consumption equal to 1% and for energy intensity equal to −1%, we obtain more-environmentally friendly results, but they are still not enough (now, the 500 ppm mark will be reached around 2050 for both standard and spatial EKC). When a growth rate near 2.5% is imposed, we can affirm that environmental sustainability will be achieved (in 2100, the CO_2 atmospheric concentrations will be roughly equal to 488 ppm in the worst scenario “Faster gy (W)/gRE = 2.5%, gEI = -2.5%” for the standard EKC). However, if income grows at a sufficiently high rate, it may hamper the improvements achieved through greater consumption of renewable energy or increases in energy efficiency (∇ *EI*), as can be observed in Tables 5, 6 for the cases of “Faster gy (W)/gRE and gEI” (three last rows for the standard and spatial EKC forecasts). Moreover, some researchers have noted that investments in renewable energy may also boost economic growth (Chien and Hu, 2008; Apergis and Payne, 2010, 2012), which could lead to greater concentrations before 2100.

7. Conclusions and policy implications

We analysed the determinants of CO_2 emissions over the period 1990–2014 for a sample of 173 countries. In addition, forecasts for global carbon dioxide emissions were conducted. We took the EKC hypothesis as our theoretical framework and augmented it by incorporating spatial relationships. Two models were estimated: a standard EKC that includes the share of renewable energy consumption and the share of the services sector in GDP with the purpose of reflecting the composition effect; with energy intensity as a proxy of technological progress; and a spatial EKC including the previous specification and both spatially lagged income and energy intensity. Neighbouring income serves to test the pollution haven hypothesis; and neighbouring energy intensity is used as a proxy for technological spillovers.

The results show that the direct EKC (changes in national non-squared and squared income) is strongly supported for all areas, except for Oceania, whose emissions increase monotonically with national per capita income. An indirect EKC (changes in neighbouring non-squared and squared income) is strongly supported for the World as a whole and for Europe and Asia. Hence, as neighbouring per capita income increases, national emissions will rise at a decreasing rate until a turning point is reached. From then onwards, further increases in neighbouring per capita income will reduce national emissions. The continent of Oceania shows the inverse relationship, an indirect U-shaped curve. We conclude that when spillover impacts are taken into account for the World as a whole, the estimated final turning point will be lower than the standard one due to long-term neighbouring influences.

The policy implications of our research can be summarised in the following five points:

(I) Economic growth by its own will not guarantee environmental sustainability. Our forecasts predict that boosting only per capita income will result in an increase of global average temperature of 2 °C by around the year 2050. Therefore, countries must allocate a substantive part of their growth to environmentally friendly sectors.

(II) Technology related to energy efficiency, must be improved in a large extent due to its impact not only in each nation, but also on

their neighbouring countries. Our estimations reveal that the second largest elasticity of carbon dioxide emissions is respect to energy intensity, regardless to the elasticity related to technological spillovers.

(III) The share of renewable energy over total energy consumption has also been proved to be relevant to reduce CO_2 emissions. Nevertheless, its impact is dimmer than the related to energy efficiency. According to our forecasts, a sustained decrease of energy intensity close to 2.5%, along with greater relative consumption of renewable energy, may guarantee environmental sustainability prior to 2100.

(IV) Finally, the degree of tertiarisation seems to be non-significant for explaining changes in CO_2 emissions in most areas.

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Appendix A. – Sample statistics

	Min.	Max.	Average	Median	Standard Dev.
e (World)	0.011	70.136	4.524	2.102	6.459
y (World)	247.437	135,318.809	15,160.898	8099.462	18,491.413
POP (World)	40834	1364270000	35,194,183.079	6524283	130,779,963.201
RE (World)	0	98.343	33.820	24.544	31.598
SVC (World)	4.141	100	55.439	56.526	15.641
EI (World)	0.426	57.988	7.000	5.206	5.644
e (Europe)	0.490	27.431	7.613	7.030	3.615
y (Europe)	1246.959	97,864.195	2,7694.786	26,456.737	16,187.834
POP (Europe)	254826	82534176	15,893,809.001	7,548,227.500	2,100,0360.120
RE (Europe)	0	77.359	16.025	10.226	15.816
SVC (Europe)	15.898	87.647	64.894	65.931	10.097
EI (Europe)	2.318	47.106	6.557	5.152	4.480
e (NA)	0.473	36.093	5.046	2.285	6.515
y (NA)	2806.602	60,675.982	15,827.448	10,525.588	13,010.000
POP (NA)	40834	318563456	21,552,444.205	1,889,367.500	62,091,460.412
RE (NA)	0	74.965	21.236	13.031	20.475
SVC (NA)	33.402	93.363	68.088	69.069	10.981
EI (NA)	1.757	21.148	5.054	3.980	3.462
e (SA)	0.494	7.608	2.562	1.927	1.602
y (SA)	2837.362	22,226.452	10,488.120	10,313.325	4441.481
POP (SA)	407472	204213133	29,766,038.100	14,472,694	47,219,840.905
RE (SA)	7.610	79.150	31.935	30.683	15.718
SVC (SA)	26.124	72.854	54.693	55.222	8.813
EI (SA)	2.343	11.584	4.532	4.215	1.625
e (Asia)	0.034	70.136	6.366	3.057	9.781
y (Asia)	728.032	135,318.809	18,983.878	6961.430	26,212.933
POP (Asia)	218000	1364270000	87,047,835.541	13999235	244,991,236.029
RE (Asia)	0	95.920	24.900	6.077	29.937
SVC (Asia)	16.560	94.240	49.621	47.305	15.040
EI (Asia)	0.426	38.335	7.711	5.597	6.154
e (Oceania)	0.222	18.200	3.135	1.002	5.021
y (Oceania)	1466.336	43,395.571	9141.407	3191.057	12,102.595
POP (Oceania)	47298	23460694	3,156,161.088	285345	5,942,375.586
RE (Oceania)	0	70.798	25.696	14.555	25.323
SVC (Oceania)	20.440	83.343	61.022	65.256	14.243
EI (Oceania)	2.484	13.189	5.665	5.353	2.189
e (Africa)	0.011	10.044	1.131	0.311	2.014
y (Africa)	247.437	40,015.819	4593.003	2107.822	5883.730
POP (Africa)	69507	176460502	16,804,162.126	8,680,346	24,401,012.760
RE (Africa)	0	98.343	62.674	76.955	30.608
SVC (Africa)	4.141	100	47.083	47.462	15.082
EI (Africa)	1.492	57.988	8.438	5.786	7.112

Appendix B. – List of countries

List of countries	
[1] Antigua and Barbuda	[88] Lithuania
[2] Algeria	[89] Liberia
[3] Azerbaijan	[90] Slovakia
[4] Albania	[91] Libyan Arab Jamahiriya
[5] Armenia	[92] Madagascar
[6] Angola	[93] Mongolia
[7] Argentina	[94] The former Yugoslav Republic of Macedonia
[8] Australia	[95] Mali
[9] Bahrain	[96] Morocco
[10] Barbados	[97] Mauritius
[11] Bermuda	[98] Mauritania
[12] Bahamas	[99] Malta
[13] Bangladesh	[100] Oman
[14] Belize	[101] Maldives
[15] Bosnia and Herzegovina	[102] Mexico
[16] Bolivia	[103] Malaysia
[17] Burma	[104] Mozambique
[18] Benin	[105] Malawi
[19] Solomon Islands	[106] Belgium
[20] Brazil	[107] Hong Kong
[21] Bulgaria	[108] Luxembourg
[22] Brunei Darussalam	[109] Macau
[23] Canada	[110] Vanuatu
[24] Cambodia	[111] Nigeria
[25] Sri Lanka	[112] Netherlands
[26] Congo	[113] Norway
[27] Democratic Republic of the Congo	[114] Nepal
[28] Burundi	[115] Suriname
[29] China	[116] Nicaragua
[30] Afghanistan	[117] New Zealand
[31] Bhutan	[118] Paraguay
[32] Chile	[119] Peru
[33] Cameroon	[120] Pakistan
[34] Chad	[121] Poland
[35] Colombia	[122] Panama
[36] Costa Rica	[123] Portugal
[37] Central African Republic	[124] Papua New Guinea
[38] Cape Verde	[125] Guinea-Bissau
[39] Cyprus	[126] Qatar
[40] Denmark	[127] Romania
[41] Djibouti	[128] Philippines
[42] Dominica	[129] Russia
[43] Dominican Republic	[130] Rwanda
[44] Ecuador	[131] Saudi Arabia
[45] Egypt	[132] Saint Kitts and Nevis
[46] Ireland	[133] Seychelles
[47] Equatorial Guinea	[134] South Africa
[48] Estonia	[135] Lesotho
[49] Eritrea	[136] Botswana
[50] El Salvador	[137] Senegal
[51] Ethiopia	[138] Slovenia
[52] Austria	[139] Sierra Leone
[53] Czech Republic	[140] Singapore
[54] Finland	[141] Spain
[55] Fiji	[142] Saint Lucia
[56] Micronesia, Federated States of	[143] Sudan
[57] France	[144] Sweden
[58] Gambia	[145] Switzerland
[59] Gabon	[146] Trinidad and Tobago
[60] Georgia	[147] Thailand
[61] Ghana	[148] Tajikistan

[62] Grenada
[63] Germany
[64] Greece
[65] Guatemala
[66] Guinea
[67] Guyana
[68] Honduras
[69] Croatia
[70] Hungary
[71] Iceland
[72] India
[73] Iran (Islamic Republic of)
[74] Italy
[75] Japan
[76] Jamaica
[77] Jordan
[78] Kenya
[79] Kyrgyzstan
[80] Kiribati
[81] Korea, Republic of
[82] Kuwait
[83] Kazakhstan
[84] Lao People's Democratic Republic
[85] Lebanon
[86] Latvia
[87] Belarus
[149] Tonga
[150] Togo
[151] Sao Tome and Principe
[152] Tunisia
[153] Turkey
[154] Turkmenistan
[155] United Republic of Tanzania
[156] Uganda
[157] United Kingdom
[158] Ukraine
[159] United States
[160] Burkina Faso
[161] Uruguay
[162] Uzbekistan
[163] Saint Vincent and the Grenadines
[164] Venezuela
[165] Viet Nam
[166] Namibia
[167] Swaziland
[168] Yemen
[169] Zambia
[170] Zimbabwe
[171] Indonesia
[172] Timor-Leste
[173] Marshall Islands

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